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Abstract

Fueled by big data, powerful and affordable computing resources, and advanced algorithms, machine learning has been explored and applied to buildings research for the past decades and has demonstrated its potential to enhance building performance. This study systematically surveyed how machine learning has been applied at different stages of building life cycle. By conducting a literature search on the Web of Knowledge platform, we found 9579 papers in this field and selected 153 papers for an in-depth review. The number of published papers is increasing year by year, with a focus on building design, operation, and control. However, no study was found using machine learning in building commissioning. There are successful pilot studies on fault detection and diagnosis of HVAC equipment and systems, load prediction, energy baseline estimate, load shape clustering, occupancy prediction, and learning occupant behaviors and energy use patterns. None of the existing studies were adopted broadly by the building industry, due to common challenges including (1) lack of large scale labeled data to train and validate the model, (2) lack of model transferability, which limits a model trained with one data-rich building to be used in another building with limited data, (3) lack of strong justification of costs and benefits of deploying machine learning, and (4) the performance might not be reliable and robust for the stated goals, as the method might work for some buildings but could not be generalized to others. Findings from the study can inform future machine learning research to improve occupant comfort, energy efficiency, demand flexibility, and resilience of buildings, as well as to inspire young researchers in the field to explore multidisciplinary approaches that integrate building science, computing science, data science, and social science.

Keywords: machine learning; artificial intelligence; buildings; building life cycle; building control; building performance

Nomenclature

Abbreviations

AMI	Advanced Metering Infrastructure
ANN	Artificial neural networks
ASHRAE	The American Society of Heating, Refrigerating and Air-Conditioning Engineers

AI	Artificial Intelligence
BIM	Building Information Modeling
BNC	Bayesian Network Classifier
CART	Classification and Regression Tree
CDW	Construction and Demolition Wastes
CEM	Combinatorial Equilibrium Modeling
CNN	Convolutional Neural Network
DT	Decision Tree
ECM	Energy Conservation Measure
EKF	Extended Kalman Filtering
EUI	Energy Use Intensity
FDD	Fault Detection and Diagnostic
FmGA	Fast messy genetic algorithm
GAN	Generative Adversarial Network
GEB	Grid-interactive efficient buildings
GHG	Green-House Gas
GPU	Graphic Processing Unit
HMM	Hidden Markov Model
HVAC	Heating, Ventilation, and Air-Conditioning
IAQ	Indoor Air Quality
IoT	Internet of Things
LDA	Linear Discriminant Analysis
LiDAR	Light Detection and Ranging
MDP	Markov Decision Process
MPC	Model Predictive Control
MLE	Maximum Likelihood Estimation
M&V	Measurement and Verification
NLP	Non-Linear Programming
O&M	Operations and Maintenance
PV	Photovoltaic
PCA	Principal Component Analysis
PID	Proportional-Integral-Derivative

RBF	Radial Basis Function
RC	Resistor Capacitor
RL	Reinforcement Learning
SOM	Self-Organizing Map
SVC	Support Vector Classifier
SVM	Support Vector Machine
TPU	Tensor Processing Unit
UKF	Unscented Kalman Filtering
UMAP	Uniform Manifold Approximation and Projection
XGBoost	Extreme Gradient Boosting

1. Introduction

Machine learning is a process by which a machine can learn on its own, without being explicitly programmed. It is an application of AI (Artificial Intelligence) that equips the system with the ability to automatically learn and improve from experience. Machine learning has advanced rapidly in the recent decade, and has been fueled by three technology trends. First, with the rapid advancement of sensing and Internet of Things (IoT) technologies, more data has been collected; with data storage becoming cheaper, much more data is being stored. As a result, a massive amount of data is available for academia and industry use. Second, machine learning-oriented chips such as GPUs (Graphic Processing Units) and TPUs (Tensor Processing Units) have been designed and produced, which provide people with better access to powerful and affordable computational resources. Third, advanced machine learning algorithms have been developed and validated. Big data, high-performance computing, and advanced machine learning algorithms together enable the advancement and application of machine learning in a diverse and wide range of fields.

One of the important research and application areas of machine learning is buildings. Buildings consume more than one-third of the global primary energy and contribute to 40% of the global greenhouse gas (GHG) emissions. Meanwhile, people spend more than 85% of their lives in buildings [1]. Therefore, delivering a high quality built environment in an energy and carbon efficient way is the key to energy conservation, decarbonizing, and occupant well-being.

Today's buildings are getting much more dynamic and complicated. They integrate traditional energy services systems for lighting; plug loads; heating, ventilation and air-conditioning (HVAC); and service hot water, as well as on-site energy generation systems such as solar photovoltaic (PV) and wind turbines, energy storage systems, and charging systems for electric vehicles. Optimal operations of such grid-interactive efficient buildings (GEBs) to achieve energy efficiency, demand flexibility, and resilience are getting much more sophisticated due to the integration of systems and uncertainty of demand and supply, as well as energy or carbon signals from the energy grid. Such needs and challenges cannot be fully addressed by the existing methods of data analytics, modeling, or simulation.

As a powerful tool, machine learning is able to (and has been used to) enhance building performance. Thousands of papers have been published in the field of using machine learning to enhance building performance. With the increasing number of papers published in this field, it is crucial to have an in-depth overview of the accomplishments and achievements, major challenges, and critical research gaps in this field. Such an overview can serve as the first significant step in determining future research directions and help to avoid reinventing the wheel. A comprehensive literature review fits well into this goal.

Several reviews have summarized relevant research. Our literature search found nine review papers published in 2019 alone. Runge & Zmeureanu (2019) [2] and Bourdeau et al. (2019) [3] reviewed studies on using machine learning for building energy consumption forecasting. Qolomany et al. (2019) [4] and Djenouri et al. (2019) [5] reviewed how machine learning and big data could be applied to smart buildings. Vázquez-Canteli & Nagy (2019) [6] and Mason, K. & Grijalva (2019) [7] reviewed how reinforcement learning, a subdomain of machine learning, could be used to enhance building control. Saha et al. (2019) [8] reviewed how data analytics could be used for occupancy sensing in buildings. Sha et al. (2019) [9] summarized how computational intelligence could be used to improve building energy system design. Guyot et al. (2019) [10] reviewed how artificial neural networks (ANNs) could be used for energy-related applications in the building sector. However, those review studies only focused on a specific stage of building life cycle (e.g., building design, building operation, and control) or on a specific application (e.g., occupant sensing, load prediction), or were limited to the use of a specific machine learning algorithm (e.g., ANN).

To address these gaps, this study was a comprehensive literature review of how machine learning has been used at different stages of the whole building life cycle, including design, construction, commissioning, operation and maintenance, control, and retrofit. Such a review can help to identify the trends and challenges of this field, as well as pinpoint research and application gaps, which are especially helpful, given that so many papers have been published each year.

To serve our research goal, we conducted the literature search through the academic search engine Web of Knowledge. Web of Knowledge is selected because it is a well-recognized database for academic articles and publications. It provides a function of advanced search that allows users to customize their search preferences. Additionally, it fits well to our literature selection criteria such as journal articles are prioritized over conference papers. We used the advanced search function of Web of Knowledge with the following topic structure (Equation 1) and keywords (Table 1). Topic A encodes the keyword *machine learning*, which might be referred to differently in different studies. Topic B specifies our interest is primarily on buildings. Topic C includes different stages in the building life cycle, from building design to retrofit.

$TS = A \text{ and } B \text{ and } C$[1] (1)

Table 1: Keywords used in the literature search

A	B	C
Machine learning	Building*	Design

[1] *TS* means *topic* in the Web of Knowledge

Artificial intelligence Data driven	House*	Construction Commissioning Operation Maintenance Control Retrofit

The symbol "" is used to search for terms in both singular and plural forms*

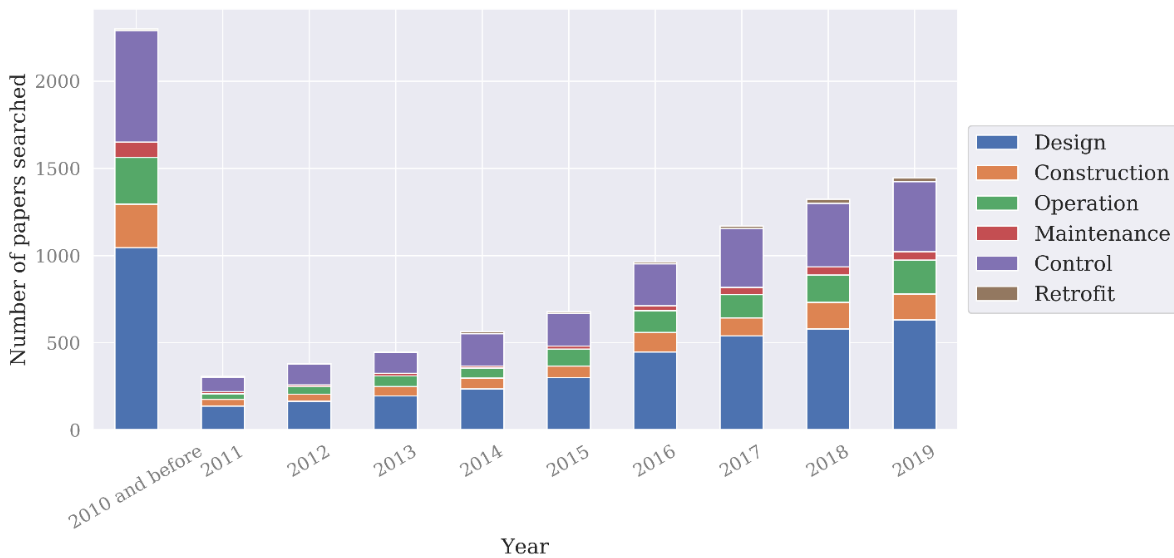

Figure 1: Literature search results[2]

As shown in Figure 1, 9579 papers were found with the prescribed keywords. Two trends could be observed. First, application of machine learning in buildings is a hot research area. Thousands of papers were published in this area each year since 2017, and there were four times as many papers published in 2019 as there were in 2011. Second, the research efforts are not equally distributed across different stages of the building life cycle. Building design has attracted the largest research interest (44%), followed by control (28%), and operation and maintenance (16%). However, no research has been conducted for building commissioning.

There are too many research articles to be exhaustively reviewed, and it is not the intent of this review to include all published work on machine learning for buildings. Therefore, we down selected papers for an in-depth review based on the following three criteria[3]:

[2] The literature search result shown here is not mutually exclusive. A paper might be counted twice if it covers different stages of building life cycle; for instance, design and construction.

[3] We acknowledge that these selection criteria might be subjective to a certain degree. Due to the large number of papers published in this area, it is challenging if not impossible for researchers to keep track on all those papers. We discussed the limitations of this review in the discussion session.

- Peer reviewed journal papers were preferred over conference papers or reports.
- Recent papers were preferred over old papers.
- Redundant papers, which use similar techniques to solve similar problems, were avoided. If there were too many papers on the same specific topic, we selected the paper based on citations, novel contribution, and the data size/quality used for machine learning.

The searched papers were evaluated by co-authors. A paper was selected by manually reading the abstract first (for majority of papers) and then the whole paper if the abstract is more relevant and methods or findings are interesting or novel. Only English language articles are considered.

As a major contribution of this article, the reviewed papers were organized according to the stages of building life cycle they are applied to. Figure 2 illustrates the overview of this review article.

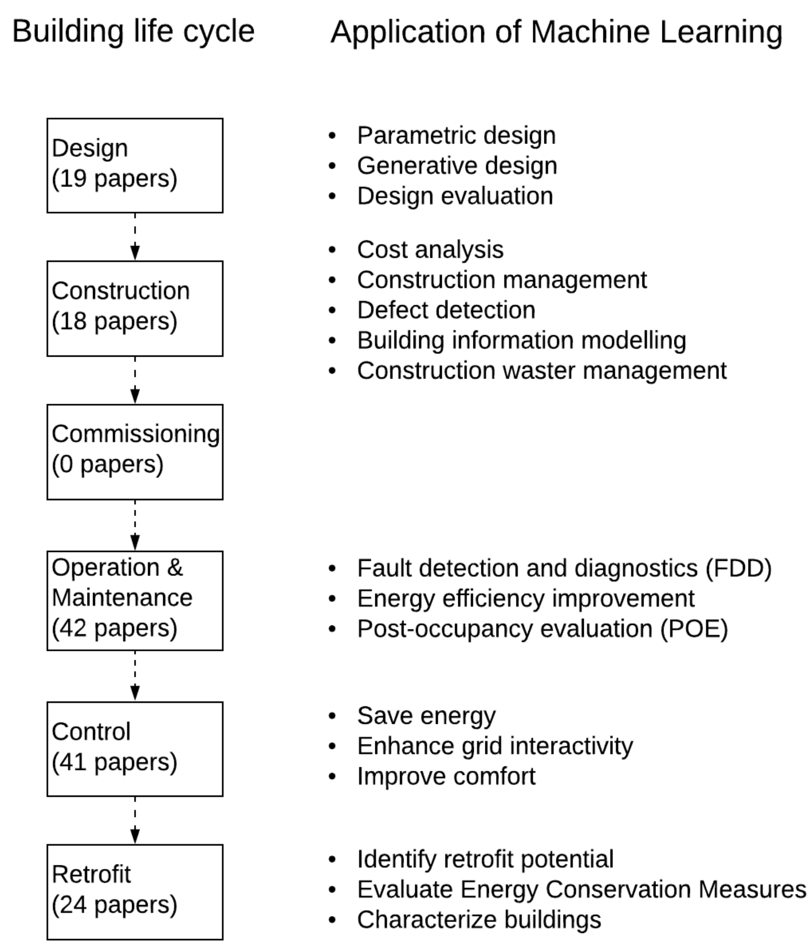

Figure 2: Overview of applications of machine learning across the building life cycle

The remainder of the paper provides a review of machine learning at each stage of the building life cycle, followed by the discussion and conclusions.

2. Machine Learning for Building Design

At the design stage of the building life cycle, artificial intelligence, machine learning, and generative design have begun to change the way architects envision and create the built environment. Building data and codes are becoming more accessible, and have reached a point where data-based design can present diverse opportunities to optimize the traditional workflow. In the recent decade, researchers have explored applying machine learning techniques to generate and evaluate design models before physically employing them in the construction. In this section, we review machine learning applications in three aspects (Table 2): (1) parametric design emulation, (2) generative design, and (3) design evaluation with supervised learning.

Table 2: Summary of machine learning algorithms applied in building design

Applications	Machine Learning Algorithms	References
Design generation and emulation	Generative Adversarial Network (GAN)	[11]–[14]
	ANN	[15]
	Clustering	[16]
Design evaluation	Plain ANN	[17]–[19]
	ANN, PCA, SVM	[20]
	Random Forest	[21], [22]

First, parametric design—applying machine learning models and blending statistical principles with computations—is a new approach that facilitates more variability in the design workflow. In the past decade, parametric design methods and tools were used in architectural and structural design for optimization purposes. The methods allow designers to not only define a final geometric solution, but also to describe the entire system and specific parameters in the system that drive different variations of the design. However, the traditional parametric design requires setting the rules to be encoded in the program, and the exploration of the design space is still limited by the abilities of human designers. Machine learning techniques have been used to emulate the hard-coded rules and parameters, unveiling the underlying phenomena behind them [15], [23]. For example, a machine learning framework was designed by Yu Zhang et al. to use principal component analysis (PCA) for interrogating, modifying, relating, transforming, and automatically generating design variables for the purpose of structural safety and daylighting environment optimization [21]. Similarly, an efficient construction form finding tool, Combinatorial Equilibrium Modeling (CEM), was designed to represent the infinite solution space of equilibrated forms, while machine learning algorithms such as Self Organizing Map (SOM) and Uniform Manifold Approximation and Projection (UMAP) were applied to analyze this design space and control the interactions between input parameters and resulting structural design [24]. These articles demonstrate the initial workflows for determining the significance of design parameters that optimize certain performance and automatically generating meaningful parameters for specific typologies.

Recent studies have focused on generative design using Generative Adversarial Network (GAN), which further automates the time-consuming process of manually implementing design rules. The technique has been successfully applied in floor plan generation, rendering, and style conversion [12], [13], [25]. For example, Huang and Zheng applied pix2pixHD, a modified version of GAN, in recognizing architectural drawings and marking rooms with different colors, to generate apartment floor plans [11]. Liu et al. applied similar algorithms to convert the rasterized floorplan image into a vector-graphics representation, allowing 3D model generations for better indoor scene visualization, direct model manipulation for architectural remodeling, and further computational applications such as data analysis [14]. The techniques also can be used in architectural style learning and conversion. For example, Chaillou developed an objective plan generator using GAN. By training and tuning an array of models on specific styles, including Baroque, Row House, Victorian Suburban House, and Manhattan Unit, a basic floor plan can be emulated to the learned style. As summarized by these articles, machine learning reveals a deeper meaning of the functional rules that define the mechanic and internal organization of the stylistic.

Using machine learning in design evaluation also helps designers with their decision-making processes. The objectives focus on space utilization, safety, energy efficiency, and occupant well-being [26], [27]. Phelan et al. described a method for predicting meeting room utilization using an ANN trained on empirical data from 56 buildings [28]. This method was able to predict meeting room usage, outperforming human designers. Another piece of research, by WeWork, was set out to identify the spatial factors that influence the success of office design empirically [29]. Using building information modeling (BIM) data and occupancy data, a machine learning model using a support vector classifier (SVC) was developed to classify the least desirable offices in their portfolio with a 60%–70% precision. Visual comfort and daylighting performance evaluation is another area that uses a computer vision method for the large-scale and automatic assessment of the building and urban visual environment, by leveraging state-of-the-art machine learning techniques (L. Liu et al. 2017; Zhou and Liu 2015; Radziszewski and Waczynska). A study conducted by Lorenz et al. adopted ANNs to predict climate-based Daylight Autonomy levels in interior spaces as an alternative to computationally expensive daylighting simulations [17]. Another study by Chatzikonstantinou and Sariyildiz compared the accuracy and computational cost of three machine-learning methods with respect to their applicability in approximating daylight autonomy and daylight glare probability. They inductively learn from simulation-derived visual comfort indicators in office spaces [22].

The advent of machine learning in design is still in its early days but offers promising potential, as we saw in the previous articles. However, that promise remains contingent on communicating the design intent and evaluation metrics to the machine. While certain design attributes, such as space accessibility, daylighting, and visual distractions, can be measured quantitatively, human preferences are still complex to measure manually [16]. Limitations of current research also includes a lack of the large amounts of data necessary to train the algorithms, the applicability of the trained algorithm to novel situations, and the black-box nature of the results. To leverage the full potential of data-driven design, future development should not only provide designers with more design options but also help them understand their design problems better through human-computer interaction.

3. Machine Learning for Building Construction

Through the literature review, we identified five applications where machine learning could help: cost analysis, construction management and documentation, defect detection, Building Information Modeling, and construction waste management. In this section, we review the application of machine learning for building construction from the above five aspects. Table 3 summarizes the major machine learning algorithms used in building construction stage.

Table 3: Summary of machine learning algorithms applied in building construction

Applications	Machine Learning Algorithms	References
Cost analysis	SVM	[32]
	Fast messy genetic algorithm (fmGA) and SVM	[33]
	Linear Regression, ANN, and SVM	[34]
House pricing prediction	Non-mating genetic algorithm	[35]
Construction object/material detection	CNN	[36], [37], [38],
Construction documentation	Photogrammetry	[39], [40], [41]
Construction defect detection	CNN	[42], [43], [44]
Building Information Modeling	SVM	[45]
	PCA, Maximum Likelihood Estimation	[46]
Construction waste management	PCA, CNN	[47]

3.1 Cost analysis

One important application of machine learning techniques in the construction phase is cost management. Predicting construction costs could help project managers identify potential problems, adopt response strategies, and better control project costs. However, accurately predicting construction costs is difficult at the planning or early stage, when the project information is limited. Tian et al. (2009) [32] presented a Support Vector Machine (SVM)-based approach to forecast the logistic cost during the construction stage, which proposed an iterative algorithm to tune SVM parameters. This method demonstrates a higher accuracy compared with conventional approaches, such as the moving average method, the exponential smoothing method, the time series decomposition method, and the regression model method. Cheng et al. (2010) [33] proposed an evolutionary SVM Inference Model to generate project cost estimation; the model fused two machine learning techniques: fast messy genetic algorithm (fmGA) and SVM. Kim et al. (2013) [34] compared the prediction accuracy of regression analysis, ANN, and SVM for construction cost prediction, and found ANN outperformed the other two techniques; however, the structure of ANN was not reported in their paper.

Rafier and Adeli (2015) [35] explored the possibility of using machine learning for housing price prediction, which is of paramount importance for construction cost planning. Rafier and Adeli (2015) [35] presented a novel and comprehensive model for estimating the price of new housing in any given city at the design phase or beginning of the construction, through an ingenious integration of a deep belief restricted Boltzmann machine and a unique non-mating genetic algorithm. The model incorporates time-dependent and seasonal variables. It also discussed how to overcome the dimensionality curse and how to make the solution of the problem amenable on standard workstations.

3.2 Construction management and documentation

Progress reporting is an essential management function for the successful delivery of construction projects. As images are more informative than text, digital photographs of a construction site are gradually replacing their traditional paper-based counterparts to record the construction process. Computer vision techniques could be used to store, process and analyze images taken from construction sites efficiently and automatically. For instance, computer vision techniques have been used to detect construction objects such as beam, column, wall and slab [36] and construction materials [37], within the image content. Zhu and Brilakis (2010) [38] proposed a two-step approach to extract material regions (e.g., concrete, steel) from the construction site images: first, dividing images into regions through image segmentation; second, calculating and classifying visual features of each region with a pre-trained classifier to determine whether the region is composed of a specific construction material or not. The detected information could be used to facilitate a more efficient indexing, classification, retrieval, and management system of construction site images, and for automated construction process monitoring.

El-Omari, S. and Moselhi (2008) [39] presented a method of integrating 3D scanning (3D images collected using Laser Distance and Ranging equipment) and photogrammetry (images collected using digital camera) in an effort to generate construction process reports, which could enhance the speed and accuracy of data collection from construction sites to support progress measurement and project control. The authors demonstrated the application of this method using a building under construction.

In addition to the construction process management, applying computer vision techniques to image data could also be used to document and preserve historical buildings. Arias et al. (2005) [40] applied computer vision techniques to analyze the close-range photogrammetry data collected from a group of Spanish monuments as a preventive method for two applications: first, detection, measurement and tracking of the temporal evolution of some structural problems detected; and second, assessing the conservation degree of the materials employed. A similar approach also has been used to document and preserve traditional agro-industrial buildings in Galicia [41].

3.3 Defect detection

Machine learning, especially image processing techniques, could be used to detect construction defects and to monitor the structural health of buildings.

Akinci et al. (2006) [42] proposed a construction quality control method through automatic construction defect detection and management. The key idea of this approach is to apply a Convolution Neural Network (CNN) to analyze laser scanner image data, and then to compare the as-built objects recognized from laser scanner images with as-planned objects to identify deviations and to assess whether the identified deviations constitute a construction defect. Zhu and Brilakis (2009) [43] applied computer vision techniques to automatically inspect concrete surface defects, such as air pockets and discoloration. This approach can locate the air pockets and discoloration regions on concrete surfaces and detect the number of air pockets and the area of discoloration regions.

Some studies specifically focus on the structural health of bridges. Jiang et al. (2008) [48] reviewed computer vision and image processing techniques that could be used to detect bridge deformation and to monitor structural tests. They argued that this non-contact, non-destructive approach could achieve an order of accuracy of one mm (0.04 in.), and save more than 50% of the labor. Zhu et al. (2010) proposed a two-step method to detect large-scale bridge concrete columns for the purpose of eventually creating an automated bridge condition assessment system. This method first employs image stitching techniques [44], to combine images containing different segments of one column into a single image, and then applies CNN to locate the bridge columns' boundary and to detect its materials.

3.4 Building Information Modeling

Building information modeling (BIM) has attracted increasing attention from both academia and industry. It is an emerging technology used to digitalize the construction industry, and is a new paradigm to store and exchange building-related data.

A BIM constructed from a CAD model does not generally capture the details of a facility as it was actually built. Laser scanners can be used to capture dense 3D measurements of a facility's as-built condition and the resulting point cloud can be manually processed to create an as-built BIM. However, this process is time-consuming, subjective, and error-prone. To solve this pain point, machine learning can be used to automatically convert raw 3D point cloud data collected from a laser scanner to BIM.

Tang et al. (2010) [49] surveyed techniques of automating the process of creating as-built BIM from laser scanner data, which could be divided into three core operations: geometric modeling, object recognition, and object relationship modeling. The methods and algorithms to represent knowledge about shape, identity, and relationships also have been outlined and summarized. Xiong et al. (2013) [45] proposed a four-step approach: first, extracting and labeling planar patches as walls, ceilings, or floors from an input point cloud through ray tracing; second, locating openings such as windows and doors by fusing measurements from different scan locations; third, estimating the shape of openings using SVM with a radial basis function (RBF) kernel; and last, filling in occluded surface regions using 3D inpainting algorithms.

The 3D point cloud data could be used not only for automatic BIM, but also for sensing the indoor household environment. Rusu et al. (2008) [46] proposed a geometrical mapping process for 3D object maps of an indoor environment, which contains the following steps: sparse outlier removal; normal and curvature estimation through Principal Component Analysis and Maximum Likelihood Estimation Sample Consensus; feature persistence analysis; feature histogram; registration to align a set of interpreted PCD views into a single point cloud model; and finally surface reconstruction

3.5 Construction waste management

Kuritcyn et al. (2015) [47] applied computer vision techniques to recognize the class of Construction and Demolition Wastes (CDW). This study proposed a method to automatically identify the CDW classes by using image recognition algorithms. Kuritcyn et al. (2015) also explored how to incorporate additional features extracted from the spectral analysis to enhance classification accuracy. Several beneficial attributes were found, such as the infrared radiation spectrum, which have discriminatory power to classify the chosen materials. The results of this study could facilitate a safer CDW recycling work environment and a higher quality in recycling.

4. Machine Learning for Building Operation and Maintenance

Buildings need to be carefully operated and maintained to sustain high performance. Day-to-day operations and maintenance (O&M) influence occupant health, energy performance, and utility cost. Modern infrastructure and technologies, such as smart technologies and appliances, advanced metering infrastructure (AMI), and advanced communication systems, have been applied in the building industry during the past decade [50]. In general, these technological improvements hold the promise of significant advances in centralized operation and management, fault diagnosis, post occupancy evaluation, and occupant comfort optimization. Meanwhile, in the past decade, the IoT has become a critical part of daily operations, deployed at a city-wide scale, and has unlocked the potential to collect real-time empirical data about the individual building component [51]. Massive amounts of building operational data are collected and stored in modern buildings, and these provide rich information for in-depth investigation and assessment of actual building operational performance [52]. Recent research has focused on applying machine learning techniques to the steady improvement of the tools operators and engineers can use to inform decision-making. In this section, we review the applications of machine learning techniques in buildings O&M for the purpose of (1) fault detection and diagnostics (FDD), (2) energy efficiency improvement, and (3) post-occupancy evaluation.

Solutions that use machine learning have been widely deployed to profile appliances and detect anomalies and failures in different components of the energy management system in buildings. Data-driven predictive analysis models can make this decision-making task simpler by minimizing manual checks and maintenance overheads. The combination of sensors and their autonomous coordination and simulation will help to predict the malfunctioned devices, equipment or systems and take appropriate actions in advance. Classification is the machine learning problem considered in most of the solutions [5]. Table 4 summarizes the major supervised learning algorithms used in building HVAC system FDD and their applications.

Table 4: Summary of machine learning algorithms applied in FDD and their applications

HVAC Components	Machine Learning Algorithms	References
Chiller	PCA	[53]–[55]
	SVM	[56]–[59]
	Linear Discriminant Analysis (LDA)	[60]

	Linear Classifier	[61], [62]
	Bayesian Network Classifier (BNC)	[63], [64]
Air-Handling Unit (AHU)	PCA	[65]
	ANN	[66]
Variable Air Volume (VAV) unit	PCA	[67]
	BNC	[68]
Variable Refrigerant Flow (VRF) system	Decision Tree (DT)	[69]
Terminal unit	SVM	[70]
Whole system	ANN	[71]

Apart from supervised learning, clustering is also applied in FDD to preprocess the time series dataset for grouping diverse system behaviors.

Armed with enormous data sets measuring actual operation and the system, machine learning can direct analytics to focus on energy and load shape benchmarking, comparisons and identifying operation patterns, and spotting energy conservation opportunities. Unsupervised learning, including clustering, association, and anomaly detection, is the most used technique for identifying the data structures, correlations, and associations in building operation conditions, occupant behaviors, and interactions among building components [72]–[78]. For example, Miller and Meggers proposed a framework to mine electrical meter data to predict operations strategy for hundreds of non-residential buildings. The framework applied feature extraction and clustering to reduce the expert intervention needed to utilize measured raw data for identifying operation behaviors, and achieved 63.6% more accuracy in operations-type recognition as compared to baselines [79]. Fan et al. proposed a gradual pattern mining method for discovering useful patterns and knowledge from building operational data as a generic approach, and they applied it in the correlation recognition of AHU cooling valve opening, hot water valve opening, and supply and return hot water temperature difference, to infer building energy efficiency enhancement opportunities [80]. They also applied this method in another case study for chiller and cooling tower control optimization [76]. Another study by Li et al. performed a clustering analysis and association rules mining method on the variable refrigerant flow systems, to identify energy consumption patterns including undercharge fault and low and high part-load ratio conditions [81].

The application of big data analytics to post-occupancy evaluations is another area of growing interest and research. The ability to mine indoor environmental data from measurement and occupant satisfaction/comfort data from surveys provides new opportunities for facility managers to more effectively respond to occupant complaints and optimize building performance. Both supervised and unsupervised learning methods have been adopted from the perspective of personal comfort learning [82]–[87]. Several elements are commonly considered within the scope of such studies, including indoor air quality (IAQ), indoor environmental (thermal, acoustic, visual, and spatial) quality, occupant health and safety, occupant comfort, and occupant complaints [88]. Kim et al. presented a novel approach for developing personal comfort models that use occupants' feedback and their heating and cooling behavior to predict an individual's thermal preference. The model development draws from field data, including personal control behavior, environmental conditions, and mechanical system settings collected from 38 occupants in an office building, and employs six machine learning algorithms for classification [89]. Ghahramania et al. introduced an online learning approach for modeling and quantifying personalized thermal comfort. A Bayesian optimal classifier was trained over 33 subjects to identify each subject's comfort condition over time (i.e., uncomfortably warm, comfortable, and uncomfortably cool), and an average accuracy of 70.14% and specificity of 76.74% were achieved [90]. Developing upon this, they also presented a hidden Markov model (HMM)-based learning method to capture personal thermal comfort using infrared thermography of the human face. The validation case study over a four-day experiment with 10 subjects demonstrated an accuracy of 82.8% for predicting uncomfortable conditions, and the approach can potentially be used for continuous monitoring of thermal comfort, to capture the variations over time [91].

Technological convergence is accelerating with the increasing deployment of IP-based endpoint devices, with a huge amount of data flowing into the building market, advocating awareness of big data management and advanced analytics techniques in the field [92]. Machine learning takes the variety of the explosive amount of building operation data and learns from it, figuring out trends and patterns for building or business owners to use. Machine learning also provides a new opportunity to leverage the widely deployed low-cost sensors, meters, smart devices, and occupant behavioral data that can be harvested to provide data-driven insights for improving building operations, occupant comfort, and productivity.

5. Machine Learning for Building Control

Conventional building control is rule-based feedback control that relies on pre-determined schedules to select the set points (such as supply air and water temperatures, zone thermostat temperature), and then applies classical control techniques (such as Proportional-Integral-Derivative [PID]) to track those set points. There are two shortcomings of this prescriptive and reactive control strategy. First, predictive information (such as weather) is not taken into consideration, leading to sub-optimal performance. Second, the control strategies are predetermined, and so not sufficiently customized to the specific building and climate, and unable to adapt to recent changes (such as retrofits) to the building.

Machine learning could be helpful to address both problems. First, machine learning could be used to predict weather, occupancy [93] and building load [94], and then take the predictive information into optimization. Second, machine learning could enable the controller to learn from the building operation data, identifying states, updating parameters, and adapting itself to any changes in the target building.

This section reviews the application of machine learning for building control. We started with the formulation of optimization problems under the building control context, then discussed how the optimization problem could be solved through machine learning. Finally, we summarized and reviewed two major approaches: Model Predictive Control (MPC) and Reinforcement Learning (RL)-based control. The structure of this section is illustrated in Figure 3. Table 5 summarizes the major machine learning algorithms used in building control stage.

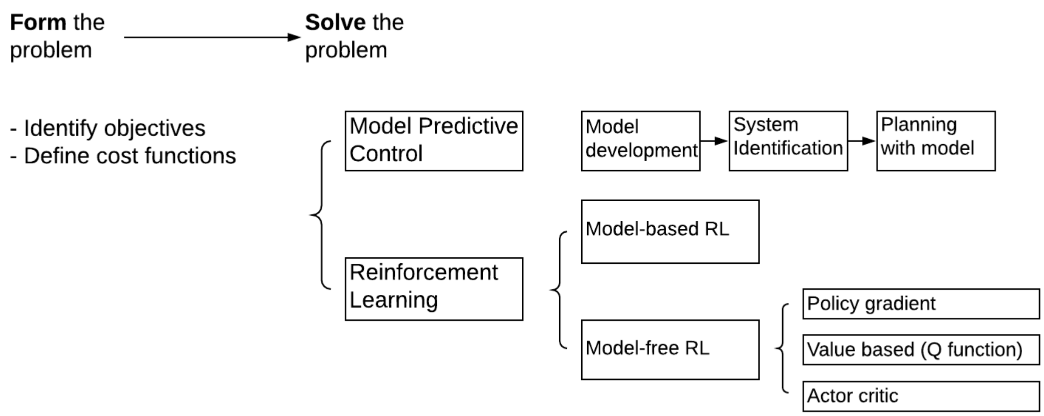

Figure 3: Review of machine learning for building control

Table 5: Summary of machine learning algorithms applied in building control

Applications	Machine Learning Algorithms	References
HVAC control	RL: Policy gradient	[95]
	MPC	[96], [97], [98], [99]
	Kalman Filter	[100], [101]
	Generic Algorithm	[102]
	RL: value based	[103], [104], [105], [106], [107], [108]
	RL: actor critic	[109], [110]
Learning building thermal dynamics for building control	RC model and regression	[97], [111], [112], [113]
	RC model and Generic Algorithm	[114]
Lighting control	RL: value based	[115]
Window control	RL: value based	[116]
Thermal Energy Storage control	Non-linear programming	[117]
	RL: value based	[118]
	RL: actor critic	[119], [120]
Hot water control	RL: value based	[121]
	RL: actor critic	[122]

Comfort improvement	Bayesian inference	[123], [124]
Home appliances scheduling	RL: value based	[125]
Heat pump operation	RL: value based	[126]

5.1 Problem formulation

The first step to apply machine learning techniques to enhance building control is to form the problem mathematically, which is more challenging than most people thought, as the building operation actually has multiple objectives in providing higher level services at lower energy costs. How to encode multiple objectives into the building control problem formulation is another question worthy of investigation when applying machine learning techniques for building control.

The first approach is to use the weighted sum of the comfort objective and the energy objective (Chen et al., 2019 [95]). The weights of the comfort and energy objectives are tunable, based on which cost needs to be more heavily valued. For instance, Chen et al. (2019) gave comfort a high value when the space was occupied but a much lower value when the space was unoccupied.

The second formation of this multi-objective optimization is to enforce one objective as a hard constraint and only leave the other for optimization. Blum et al. (2019) [96] applied this approach in his study: given an acceptable temperature range, the energy consumption is minimized. The comfort range, i.e., the lower and upper bound of temperature T_{lower}, and T_{upper}, might come from current standards, statistical analysis on a large open-source database [123], or directly from building users' votes [124]. Similarly, the multi-objective optimization problem could be formulated as enforcing the energy consumption as a hard constraint while maximizing the comfort benefit, which could be interpreted as: given the energy consumption budget, the occupants' comfort is maximized.

The first formulation is also called a "soft constraint," as the optimizer could violate the comfort or energy constraint; however, those violations are associated with a cost. The "hard constraint" and "soft constraint" formations are actually not distinguishable. When the value of η approaches infinity, the cost of violating the comfort constraints is too high to bear. In this case, the optimizer would automatically avoid violating the comfort constraint, and consider the comfort constraint as a hard constraint; in which case the two formulations of the optimization problem are essentially the same.

In addition to the goal of maximizing thermal comfort and minimizing energy consumption, there are some other common goals for building control. In the comfort side, thermal comfort is the most frequent control objective. In addition to thermal comfort, visual comfort [115] and indoor air quality [116] have been considered in previous studies. Other similar goals complementary to energy conservation include minimizing carbon emission, minimizing operation costs [117], and enhancing grid interactivity (such as load shifting, or maximizing the self-consumption of the local PV production [121]). Those goals could be encoded easily by multiplying the energy consumption with a time-of-use weight, which might be a time-of-use utility rate for the cost optimization problem or a time-of-use carbon emission rate for carbon emission minimization.

5.2 Model Predictive Control (MPC)

Model development

The first step for MPC is to develop the model that can capture the buildings' thermal dynamics. In the MPC domain, there are usually two approaches to develop the model: (1) the thermal resistance and thermal capacity network (RC network) and (2) the state space method.

The RC network approach simplifies the thermal behavior of building components (e.g., exterior wall, interior wall) as thermal resistance and thermal capacitance [97]. And accordingly, the thermal dynamics of buildings could be simulated with a network of thermal resistance and thermal capacitance. An important concept of the RC network is the model order, i.e., how many thermal resistances and thermal capacitances are there in a network. Different modelers selected different model orders, ranging from 1R1C [111], 2R2C [112], 3R2C [114], 4R2C [113], 3R3C [96], to very complicated 19R13C [98]. The selection of model order is a trade-off between model accuracy and computational efficiency. However, too complicated models might suffer from the over-fitting problem.

The second approach to model building thermal dynamics is the state space method, which is widely used in classical control theories. The state space approach classifies the building variables into three categories: (1) state (such as room temperature), (2) control action (such as supply airflow rate), and (3) disturbance (such as solar radiation and outdoor air temperature). The states of the next time step (*t+1*) can be predicted by the states, actions, and disturbances of the current step (*t*), along with the transfer function A, B_u, B_d. Similar to the RC network, there are also many variations of state space. Issues needing to be considered at the modeling stage include: (1) whether the transfer function is linear, (2) whether the Markov property holds; that is, is it necessary to include historical states (not only *t*, but also *t-1*, *t-2,* etc.) to calculate the states of time step *t+1* [99], and (3) which variables should be selected as states and disturbances, and whether or not it is necessary to include hidden states as well (those states not directly measured such as wall temperature). The most straightforward and simplest representation of the state space method is to consider the building thermal dynamics as a linear and Markovian process [95].

The difference between the RC network and the state-space method is that the RC network has physics representation, and the parameters of R and C have clear physical implications. Contrarily, the state space method is just a mathematical representation of thermal dynamics, which is more difficult to be interpreted. However, the distinction between these two approaches becomes vague once the order of the RC model increases.

In the MPC framework, only the model form is selected and determined in the model development stage, and the values of parameters are learned from data. For instance, if the RC network is used, the modeler needs to specify the model order, but the value of R and C are unknown yet, and that will be learned in the system identification stage.

System identification

Once the model is developed, the next step is to infer the model parameters with the collected data. As the model parameters are identified from the latest observations, any changes that might influence the building's thermal dynamics could be captured and reflected by the varying parameter. Thus, the controller is self-adaptive.

Different approaches could be used for system identification. Kalman Filtering is one choice. Standard Kalman filtering includes two steps [127]: (1) predict the next state based on the mathematical or physical model, and (2) update the state by the weighted sum of the prediction and new observation. The idea of combining the physics-based model and new observations to update the state makes Kalman filtering a natural fit for self-adaptive parameter identification. However, the standard Kalman filtering could only apply to linear systems, as the closed form of Kalman gain is under the condition of normal distribution and linear transformation. To deal with the nonlinearity of building systems, variations of Kalman filtering—for instance, an extended Kalman filter (EKF) and unscented Kalman filtering (UKF)—are proposed. Fux et al. (2014) [100] used an EKF to identify the hidden states and model parameters. EKF solves the nonlinearity by using Taylor expansion to construct a linear approximation of the nonlinear system. Maasoumy et al. (2014) applied UKF for state estimation and parameter identification. UKF solves the nonlinearity by acknowledging the nonlinearity transformation between time steps, but using a normal distribution to approximate the real distribution of the to-be-identified states/parameters after the transformation. It was found that the UKF outperforms EKF for building parameter estimation [101].

The second approach is to reframe the system identification problem as an ordinary optimization problem, i.e. to find the value of parameters that could minimize the difference between the predicted and measured states of the next time step. From machine learning point of view, this is a typical supervised learning problem. The only difference between system identification problem and other regression problems is whether and how the physics is encoded.

The optimization problem could be solved through both gradient-free and gradient-based optimization techniques. As an example of the gradient-free approach, Lee and Braun [102] used a Genetic Algorithm to search reasonable values of the to-be-identified parameters, and then used a local nonlinear regression method to further improve the parameter estimates by minimizing the root-mean-squared prediction error. Arendt et al. (2019) [128] developed and open-sourced a Python package, ModestPy, to solve the system identification problem through gradient-free methods such as a genetic algorithm and a generalized pattern search. The gradient-based optimization considers the optimization problem as a Non-Linear Programming (NLP). Harb et al. (2016) [113] utilized the optimization library of MATLAB for model identification. Blum et al. (2018) [96] used the optimization framework implemented with JModelica for model identification, which used the direct collocation discretization method of Optimica to set up an NLP, use CasADi for algorithmic differentiation, and solve the NLP with the MA27 linear solver developed by IPOPT.

Planning with the model

Once the model is developed and identified from the collected data, the next step is to use it for planning, i.e., find the optimal control sequence given the building dynamics and optimization goals. In the MPC field, there are two approaches for planning: (1) the shooting method and (2) the collocation method, as summarized in Table 6.

The shooting method forms the planning process as an unconstrained optimization problem, that selects the optimized action over the time horizon. Theoretically, the optimization problem could be solved efficiently by using differentiate via backpropagation. However, in practice, directly solving Equation 3 might be problematic, especially when the control sequence T increases. The problem of a vanishing or exploding gradient might happen with increasing T, similar to what happened in the Recurrent Neural Network. Therefore, shooting method is not widely used.

The collocation method forms the planning process as a constraint optimization problem, which optimizes over both actions and states, which is constrained by the building dynamics. This formation is very typical in the convex optimization domain, and we could refer to the mature NLP tools to solve this problem. But one thing to keep in mind is that NLP could find the global optimal only when the problem is convex, which is unlikely to be the case in the building field. Therefore, we might need to try multiple initial guesses to find the global optimal. For instance, Blum et al. (2018) [96] used Latin Hypercube Sampling to more efficiently and comprehensively test different initial guesses to search for the global optimal.

Table 6: Difference between shooting and collocation method

	Optimized variable	Constraint or not
Shooting	Actions only	Unconstraint optimization
Collocation	Both actions and states	Constraint optimization

Before concluding our discussion on MPC, it is worthwhile to point out that the two-step (system identification and control optimization) approach is valid based on the implicit assumption of the optimized parameter θ associated with the minimized prediction error that could result in the optimal control action [95]. However, the recent Chen et al. (2019) study argued that this assumption might not necessarily be true, i.e., the small prediction error does not translate to good control performance. Therefore, a new framework called Differentiable MPC for end-to-end control has been proposed [129]. In this framework, the system identification step was integrated or "skipped"' (that's why it was called end-to-end) into the control optimization step, which was found to have better performance in the field of building control [95].

5.3 Reinforcement Learning-based control

Reinforcement learning (RL) is another approach that can be used to find a building's optimal control strategy. RL is a machine learning approach that adapts to different environments by learning a control policy through direct interaction with the environment [130]. With the rapid development of software (new algorithms) and hardware (high computational power), RL has achieved success in many fields and has been used in the building control field. Vázquez-Canteli and Nagy's review paper (2019) found new publications for applying RL to building control have increased significantly since 2015 [6].

Reinforcement learning forms the building control problem as a Markov Decision Process (MDP). It is constituted of the state space S; action space A; observation space O; the transition operator T, mapping the state and action of current time step to the state of the next time step; the emission probability ε, mapping the state to the observation; and the reward function r, mapping the state and action to the reward. It is worth mentioning that the symbolic system of RL is different from that of MPC. In this review paper, to show our respect to both subjects, we use different symbolic systems that are consistent with both the MPC- and RL-based control, and summarize the differences in Table 7.

Table 7: Symbolic system of MPC- and RL-based control

	State	Control Action	Objective
MPC	x	u	cost function c

RL	*s*	*a*	reward function *r*

Similar to MPC, the goal of RL-based control is to find a mapping from states to actions that maximize the rewards. The mapping from states to actions is called policy. The sequence of states and actions $s_1, a_1, \ldots s_T, a_T$ is also called trajectory ୮, which is determined by both the policy and the environment dynamics.

To solve the above optimization problem, two approaches are available in the RL domain: model-based RL and model-free RL.

Model-based RL

The term model in the RL framework refers to two specific functions: the transition function $p(s_{t+1}|s_t, a_t)$ and the reward function $r(s_t, a_t)$, which explicitly represents the dynamic behaviors of the environment. Model-based RL refers to the approach where we learn $p(s_{t+1}|s_t, a_t)$ and $r(s_t, a_t)$ first, and then use the learned transition and reward functions for planning. Model-based RL is somewhat similar to MPC. Learning the transition and reward functions is similar to the system identification step of MPC. In the planning stage, shooting and collocation methods could be used for both model-based RL and MPC.

In our literature search, we did not find any studies using model-based RL to solve the building control problem. Because model-based RL is strongly affected by the quality of the model, a huge amount of time [103], effort, and data are needed to develop a high-fidelity model. This makes model-based RL expertise demanding, not cost-effective, and sometimes even impossible, because the building operational data might be insufficient.

Model-free RL

The constraints of model-based RL could be solved by model-free RL, which makes model-free RL much more attractive in the field of building control. Model-free RL does not bother to learn the transition and reward function. In the model-free RL family, there are three types of algorithms: policy gradient, value-based, and actor-critic.

a) Policy gradient

The idea of a policy gradient is straightforward. As the goal of RL is to maximize the expectation of the cumulated rewards, a natural thought is to find the gradient of the objective function (expectation of the cumulated rewards) with respect to the policy parameter θ, and then based on gradient to adjust the parameter. With the help of automatic differentiation package[131] (such as TensorFlow, Pytorch, etc.), policy gradient could be easily implemented.

Policy gradient has a clear implication, i.e. to adjust the policy parameter θ to make those actions associated with higher rewards more likely to happen. However, policy gradient has some constraints: high variance, not easy to converge, and etc. Therefore, the policy gradient is not widely used in building control. The only literature we found using the policy gradient is Chen et al. (2019), who use a policy gradient to control supply airflow rate of an AHU and supply water temperature of floor heating, which achieves 7%–17% energy conservation compared with the benchmark [95].

b) Value-based

The value-based method adopted a different approach, which does not rely on parameterized policy $\pi_\theta(a_t|s_t)$. Instead, a value-based RL estimates the value function of the state $V_\phi(s_t)$ or state-action pair $Q_{\phi}(s_t, a_t)$. Once the value function is known, the policy is as simple as selecting the most rewarding action. Therefore, the key problem in the value-based approach is how to estimate the value function accurately.

The way to estimate the value function is through iteration. The Bellman Equation allows us to represent the value functions in the iterative form (using the next time step's value to calculate the current time step). There are two types of value function: the state value function, and the state-action pair value function. The state value function $V_{\phi}(s_t)$ evaluates the value of state s_t, while the state-action pair value function $Q_{\phi}(s_t, a_t)$ evaluates the value of taking action a_t at state s_t. It turns out that state-action value function $Q_{\phi}(s_t, a_t)$ is much more widely used than the state value function $V_{\phi}(s_t)$, as $Q_{\phi}(s_t, a_t)$ could be directly used to determine the policy $\pi_{\theta}(a_t|s_t) = \max_{a_t} Q_{\phi}(s_t, a_t)$. As the state-action value function is denoted by Q, the state-action value function-based RL is also called Q-learning, which dominates the value-based RL family.

The majority of RL for building control adopts the Q value function-based approach, which could be further categorized based on the form of Q function. If the states and actions are discrete, the Q function could be represented in the form of a table. For instance, Liu and Henze (2007) [104] used tabular Q-learning to control the temperature set point and the operation of thermal storage. May (2019) [116] used tabular Q-learning to control the window opening state (on or off) and found significant improvement on the occupant's comfort. However, if the states and actions are continuous or in high dimensions, the Q table is unable or inefficient to represent the Q function. Two approaches are proposed to address this issue. The first is fuzzy Q-learning, which uses fuzzy rules to map the continuous state-action space to discrete state-action pairs. Yu and Dexter (2010) applied fuzzy Q-learning to control an HVAC set point [105], and Zhou et al. (2019) used fuzzy Q-learning to manage the smart grid [106]. The second approach is to use value function approximation, i.e., using some approximation function to regress the mapping between state-action pairs to values. The simplest approximation function is just the linear function, which was used by Dalamagkidis et al. (2007) to control the HVAC operation [107]; and by Bahrami et al. (2017) to optimize the scheduling of home appliances [125]. Leurs et al. (2016) [108] used the random forest to approximate the Q function for HVAC control to shave the maximum feed-in power of a PV system into the grid. Random forest was used to approximate a Q function in the Ruelens et al. (2015) study to control a heat pump's operation [126]. Similarly, in the De Somer et al. (2017) study of an RL controller for a domestic hot water heater, random forest was also used to approximate the Q function [121]. With the development of deep learning, a more popular way to approximate the value function is to use a deep neural network, which is also referred to as Deep Reinforcement Learning (DRL). An example is the Vázquez-Canteli et al. (2019) study to control the thermal storage of a campus, i.e., the tank temperature and when to charge and discharge the tank [118].

c) Actor-critic

The third method in the model-free RL family is actor-critic, which has both parametrized policy $\pi_{\theta}(a_t|s_t)$ and value function $Q_{\phi}(s_t, a_t)$. The idea of actor-critic is similar to the policy gradient, which is to adjust the policy parameter θ to make good actions (actions with higher rewards) happen more frequently. The difference between the actor-critic and policy gradient approaches lies on how to quantify the goodness of an action. In the policy gradient, the policy is evaluated by accumulative rewards of a function $\sum_{t=1}^{T} r(s_t, a_t)$. However, the sequential decision making is always associated with randomness, the accumulated rewards of one sample ($\sum_{t=1}^{T} r(s_t, a_t)$) is an unbiased but high variant estimation of the true value of taking a_t at s_t. Actor-critic comes to solve this problem by using $Q_\phi(s_t, a_t)$ to replace $\sum_{t=1}^{T} r(s_t, a_t)$ as a more robust estimation of the true value. In the field of building control, actor-critic is not very popular, as it has both parameterized policy function and value function, which complicates the computation.

Table 8 summarizes three major model-free Reinforcement Learning algorithms.

Table 8: Three model-free Reinforcement Learning algorithms

	$\pi_\theta(a_t \mid s_t)$	$V_\phi(s_t)$ or $Q_\phi(s_t, a_t)$	Popularity
Policy gradient	√	×	Not popular
Value-based	×	√	Popular
Actor-critic	√	√	Not popular

One advantage of the actor-critic method is it could encode expert knowledge or some form of pre-training in the actor network [110] by storing and reusing the weights stored in the actor network; rather than training from scratch by just randomly initializing the weights of the actor network. Actor-critic was first introduced by Du and Fei in 2008 to the building control field for the HVAC control purpose [109]. After that, Actor-critic was used by Fuselli et al. (2013) [119] and Wei et al. (2014) [120] for energy storage control; by Al-Jabery et al. (2016) [122] for domestic hot water control; by Zhang et al. (2017) for campus-level district heating system control [110]; and by Bahrami et al. (2017) [125] for the scheduling of smart home appliances.

6. Machine Learning for Building Retrofit

Building retrofit is a crucial way to reduce the energy consumption and GHG emissions of buildings. However, the whole process of building retrofit requires continuous efforts, including accessing the current performance of the building, identifying the most applicable ECMs, and post-retrofit evaluation, which can be limited by the access to the detailed building information and the onsite operation. Hence, machine learning kicks in to help automate, simplify, and generalize the process. Table 9 summarizes the machine learning algorithms used in papers that are reviewed in this section.

Table 9: Summary of machine learning algorithms applied in building retrofit

Applications	Machine Learning Algorithms	References
Identify retrofit potential	Decision Tree	[132], [140]
	Clustering and ANN	[19]
	Clustering	[133]
	Random Forest	[134]
	Linear Regression	[135]
	Linear Regression and PCA	[136]

	Gradient Boosting	[137]
	Linear Regression and Clustering	[138]
	Gradient Boosting and Clustering	[139]
	ANN	[141]
Evaluate energy conservation measures	ANN, SVM, K-Nearest Neighbors, and Linear Regression	[143]
	ANN	[144]
	Gradient Boosting and Linear Regression	[145]
Characterize buildings	Random Forest	[150]
	SVM	[151]
	CNN	[152]
	Boosted Decision Trees	[153]
	SVM	[154]

6.1 Identify retrofit potential

Usually, building retrofit planning requires detailed energy audits, which are time-consuming. As the audit data accumulates, machine learning methods will be feasible to explore the underlying patterns of the data to support the generalization of the retrofit planning to large building stocks. Benefitting from the New York City's energy audit mandates, in one case study [132] the public audit data of more than 1100 buildings were used to train a falling rule list classifier (a form of decision tree) to predict the eligible energy conservation measures (ECMs) for a certain building based on its characteristics, such as type, build year, envelope, and system type, among others. This helps stakeholders prioritize the most-likely retrofit candidates. To target a large number of buildings, usually clustering methods will be used to identify similar buildings with respect to energy performance, and then strategies will be developed for each group. For example, Re Cecconi et al. used the Building Energy Certification open database of Italy to evaluate the energy savings potentials of public school buildings [19]. School buildings were first clustered according to their age and the envelope performance. Then, for each group, specific suitable retrofit strategies were defined to allow the retrofit of homogeneous classes of buildings, and an ANN was implemented to evaluate the energy saving potentials. Instead of clustering buildings based on their physical attributes, another case study characterized buildings directly on their responses to certain retrofit measures [133]. Six measures were defined, and the carbon dioxide (CO_2) reduction of each building was estimated based on the geometric, construction, and energy consumption information of the building. More than 300 buildings were clustered into five groups in terms of the cost-effectiveness of different measures, which simplified the strategy development of the whole building block. Temporal features of energy consumption can also be used to predict the success of the retrofit. With smart meter data of 1600 buildings that have ECMs implemented in between, temporal features such as shape and magnitude behavior of buildings can be extracted to predict the success level of the ECMs with some machine learning classifier [134].

Benchmarking is another useful method that can be used to evaluate building energy performance and thus to identify buildings that need retrofits. Though ENERGY STAR is widely used for commercial building benchmarking in the United States, it is based on a linear regression model developed on the Commercial Building Energy Consumption Survey (CBECS) dataset, which contains a limited number of nationally representative buildings and is not updated frequently. Hence, many efforts have been made to create a better benchmarking index in terms of accuracy, representativeness, and interpretability. Some methods still use linear models but with various improvements [135], [136]. Moreover, nonlinear regression models are widely used to capture the complex underlying relationship between the energy performance and building attributes. For example, gradient boosted trees are used to enhance the existing ENERGY STAR calculations [137]. Many other studies are also using clustering algorithms or combining regression models with clustering models to divide buildings into comparable groups to obtain more solid benchmarking results. For instance, Gao and Malkawi first used a stepwise linear regression for feature selection, and then an applied K-means algorithm to cluster buildings into several groups. Thus buildings in each cluster were benchmarked against the group centroid [138]. Papadopoulos and Kontokosta [139] used XGBoost (gradient boosting) to model the energy use intensity (EUI) of residential buildings, and also used the K-means method to assign grades to buildings based on their ratio of the reported EUI divided by predicted EUI. Another study used a CART (classification and regression tree) model to partition buildings into similar groups and SFA (stochastic frontier analysis) was applied to each group to determine the potential maximum energy efficiency [140].

Quite surprisingly, advanced machine learning methods such as ANN have been adopted in this field for quite a long time. Yalcintas used ANN to predict building EUI as benchmarking models in 2006 [141]. Data used as inputs, such as plug load density, lighting type, and HVAC type, were collected from 60 buildings. Actually, very few more advanced machine learning methods were applied for benchmarking after that. Most studies focus on improving the interpretability or robustness of the benchmarking index, or leveraging larger and higher-quality building energy datasets.

6.2 Evaluate energy conservation measures

Measurement and verification (M&V) is one of the critical processes used to evaluate the effectiveness of ECMs. The term “M&V 2.0” is being used in recent years to describe the automated and streamlined approach that uses large datasets and computational automation for the M&V process, where machine learning models are playing an increasingly important role [142]. Colm et al. [143] develop a platform using machine learning methods to enable automated, accurate, and reliable quantifications of energy savings in the M&V process. A mixed model using ANN, SVM, k-nearest neighbors, and multiple ordinary least squares regression was adopted to model the baseline energy consumption. Ascione et al. developed two ANN families to predict the energy performance and thermal comfort of the existing building stocks and buildings where ECMs are applied, to replace the traditional building simulation tools [144]. Another study investigated both the gradient boosting model and linear regression model on their ability to predict the energy consumption after implementation of ECMs [145]. It is claimed that this type of model is especially suitable for ECMs with less than 10% savings, where the installation of submeters for M&V is not cost-effective.

The major application of machine learning in M&V is the energy model that predicts the energy performance of the building before and after ECMs are implemented. Within the scope of M&V, Granderson et al. proposed a testing procedure and metrics to access the modern whole building M&V methods, and ten baseline energy models were evaluated with smart meter data [146]. Beyond the scope of M&V, energy modeling with machine learning methods is a mature field already, with many extensive reviews [147]–[149], so a detailed review will not be included here.

6.3 Characterize buildings

For building energy modeling, machine learning is also widely used to extract building features to provide input for the model. The inputs are often the remote sensing images or the street view images. For example, one study used Light Detection and Ranging (LiDAR)-derived building morphology attributes to predict building age with random forests [150]. Another case study used SVM to predict the architectural building type form the building features, including 2D footprints, heights, etc. [151]. In addition, street view images were also used to extract detailed building information. Kang et al. used CNNs to predict building functionality from freely available street view images. The semantic segmentation of the building facades also has been well-studied [152], [153] and the algorithm used tends to evolve from traditional machine learning algorithms to deep learning methods. The result of the façade segmentation can be served to extract features related to envelopes including the window-to-wall ratio and the window type, etc. For example, the material type of the surface can be classified using SVMs based on the segmentation of building façade components [154].

To summarize, both supervised and unsupervised machine learning models are widely used in the building retrofit process, including building benchmarking, evaluating ECMs, and characterizing buildings, and they provide major assistance with the generalization, automation, or simplification of the process. The applications in recent years largely benefit from more available data. The popularization of smart meters and other sensors simplify data collection, and the open data initiatives in many major cities such as New York City, San Francisco, and Seattle make large scale building audit datasets accessible, facilitating the development of data-driven methods.

7. Discussion and Conclusions

Fueled by big data, powerful and affordable computing resources, and advanced algorithms, the application of machine learning to enhance building performance has attracted increasing research attention. We reviewed the research and applications of machine learning across all major stages of the building life cycle: design, construction, operation and maintenance, control, and retrofit.

Although building commissioning is an important step of the building life cycle, to ensure building design meets the intent, no studies applying machine learning to building commissioning were found. Also, no significant study was found using natural language processing techniques to extract useful information from a city's public dataset of building permits, which contain important data on retrofits and changes to buildings that could be used to improve building energy modeling and analysis.

Although machine learning has been used extensively in the building sector, several limitations and gaps were identified. First, most studies are still in the research and development phase, and very few have been adopted by the industry. Possible reasons include: (1) lack of labeled data to train the model; (2) lack of model transferability, which limits a model trained with one building to be used in another; (3) the benefits of machine learning are unable to justify the costs of its implementation and (4) the performance might not be reliable and robust for the stated goals, as the method might work for some buildings but could not be generalized to others. More encouraging and mature applications in this field are needed. Second, different machine learning methods and approaches are trained and validated on different datasets in different studies, which makes results difficult to compare or benchmark across studies. As a result, almost every study claimed to deliver better performance compared with peer studies. A fair playing field with a large scale open-source dataset is needed to enhance comparability between studies by testing different methods on a uniform dataset. Some preliminary efforts in this direction include the ASHRAE Global Thermal Comfort Database [155], the Building Data Genome Project [156], and the recently launched ASHRAE Great Energy Predictor III at the Kaggle platform, which includes multi-year smart meter data for 1500 buildings. Third, one limitation of machine learning lies in its interpretability of results. Machine learning adopts the data-driven approach, which is a black-box model, so what's happening inside the model is unclear to model users and even model developers. A potential solution to this problem is to integrate the data-driven black-box model with the physics-based white-box model by encoding physical domain knowledge into the data-driven model.

The application of machine learning in buildings is a hot research area, so thousands of papers have been published on the subject each year since 2017. Huge efforts are necessary for researchers to follow the latest developments in this field, and a dedicated literature review is needed to save researchers' time. In 2019 alone, nine review papers on this topic were published.

As the number of papers published in this area is too large to be exhaustively reviewed, we proposed three criteria to select the papers for review in this study: journal papers are preferred over conference papers; recent papers are preferred over older papers; if multiple papers are similar (using similar machine learning techniques for similar applications), papers with higher citation, novel contribution and better quality datasets were selected for review. We acknowledged that the third criterion, although based on authors' experience and domain knowledge, is subjective, especially in terms of judging the novelty and data quality, which constitutes a major limitation of this study. With the increasing research interest and publications, it is challenging for us and other researchers to follow the recent progress of this field. To address this problem, we believe Natural Language Processing could be applied to the literature review process to help researchers more efficiently track the most recent research hot topics, trends, and progress [157].

To the best of the authors' knowledge, this paper is the first literature review that provides a comprehensive summary of applications of machine learning across different stages of the building life cycle. We identified both the progress and research gaps on this topic. These findings can inform future research on machine learning to improve occupant well-being and the energy efficiency, flexibility, and resilience of buildings. We envision the advances in big data, powerful computing, and artificial intelligence will enable the creation of digital twins of buildings that make it possible to optimize the building performance across the building life cycle, integrating multidisciplinary sciences of building science, computing science, data science, and social science.

Declaration of competing interest

All co-authors declare there is no conflict of interest in the reported work.

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